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On The Classification of Binary Space Shift Keying Modulation

Mengüç Öner

***Abstract*—Blind and non-cooperative classification of the modulation employed in signals originating from unknown or partly known sources has widespread applications in civilian and military contexts. One of the most recent and interesting approaches to digital modulation which has been enabled by multiantenna transceivers is the spatial modulation, where the indices of the transmit antennas activated in a given symbol period are utilized to transmit information bits. Clearly, existing modulation classification methods, designed for the identification of conventional modulation types, are not capable of classifying the family of spatially modulated signals that make use of the space dimension. In this work, for the first time in the literature, a modulation classification method is proposed for a modulation type belonging to the family of Spatial Modulations: the Binary Space Shift Keying modulation (BSSK).**

***Keywords*—MIMO, space shift keying, modulation classification.**

I. Introduction

Automatic Modulation Classification (AMC), i.e. the identification of the modulation type employed in unknown or partly known communication signals corrupted by noise and fading, has traditionally found application in the military context, where the blind and non-cooperative analysis and identification of signals from hostile transmitters is a crucial task in signal interception, radio surveillance, interference identification and mitigation, and electronic warfare. In the civilian context, the AMC is expected to play a crucial role in the spectral awareness of Cognitive Radio (CR) systems [1].

A multiple input multiple output (MIMO) system is characterized by the availability of multiple antennas for transmission and reception, which provides additional degrees of freedom for designing efficient signalling structures for transmitting information compared to traditional single antenna (SISO) systems. Thus, AMC for MIMO systems is generally a more challenging task compared to the SISO case, and research in this particular field has been emerging only in the last couple of years (see, for example, [1], [2], [3], [4]).

One of the most recent and interesting transmission methods that has been enabled by the multiantenna nature of MIMO transceivers is the Spatial Modulation (SpM), where the indices of the transmit antennas, from which energy is being transmitted in a given symbol period, are utilized to transmit information bits, making use of the space dimension for conveying information. This leads to a simpler transceiver design and a higher energy efficiency due to the fact that only a single antenna is active at a given instant, and, furthermore, to a higher spectral efficiency compared to conventional MIMO systems employing orthogonal space-time block codes [5].

Mengüç Öner is with University of Sussex, Brighton, UK (e-mail: m.m.oner@sussex.ac.uk).

Existing AMC approaches in the literature are designed solely for the identification of conventional modulation schemes based on modulating the amplitude, phase or the frequency of a sinusoidal carrier for transmission of information. As such, they cannot be directly applied to the family of SpM that makes use of the space dimension by modulating the antenna index, hence, the AMC problem needs to be reconsidered for SpM signals. In this work, we consider, for the first time in the literature, the classification of a modulation belonging to the family of spatial modulations, the binary space shift keying (BSSK). We extend the likelihood based AMC approach in [6] to include BSSK by considering the hypothesis corresponding to BSSK as two distinct equiprobable sub-hypotheses, and deciding for the BSSK if any of the two sub-hypotheses is chosen, which enables the blind and non-cooperative classification of the BSSK in absence of a-priori information on the channel matrix and the SNR, leading to a novel maximum a-posteriori (MAP) MIMO AMC algorithm.

II. System Model and Problem Formulation

We consider a MIMO system with N_t transmit and N_r receive antennas. The received signal vector of length N_r $\mathbf{y}[k] = [y_1[k], ..., y_{N_r}[k]]^T$ at time instant k is given as

$$\mathbf{y}[k] = \mathbf{H}\mathbf{s}[k] + \mathbf{w}[k]\,, \tag{1}$$

where $\mathbf{s}[k] = [s_1[k], ..., s_{N_t}[k]]^T$ is the modulated transmit vector, $s_i[k]$ representing the sequence transmitted from the i'th antenna, $\mathbf{w}[k]$ is the complex valued circular AWGN vector with a variance of σ^2 and $\mathbf{H}$ is the $N_r \times N_t$ MIMO channel matrix with elements modeled as mutually independent zero mean unit variance complex Gaussian random variables representing a flat block fading channel.

AMC is a multiple hypothesis testing problem where each hypothesis corresponds to a modulation type in a given set of candidate modulation types $M_j \in \mathcal{M}$. The decision $\hat{M}$ made by the classifier on the transmitted modulation type is based on an observed signal block $\mathbf{Y} = [\mathbf{y}[0], \ldots, \mathbf{y}[N-1]]$ of length N. Assuming that $\mathbf{s}[k]$ is an independent and identically distributed vector sequence belonging to a discrete alphabet specified by the employed modulation type, the average likelihood function (ALF) of $\mathbf{Y}$ is given as [6]:

$$\Lambda(\mathbf{Y}|\mathbf{H}, \sigma^2, M_j) = \frac{1}{(K_{M_j})^N (\pi\sigma^2)^{N_r}} \times \prod_{k=0}^{(N-1)} \sum_{\mathbf{s}^{(j)} \in M_j} \exp\Big(\frac{-1}{\sigma^2}|\mathbf{y}[k] - \mathbf{H}\mathbf{s}^{(j)}|^2\Big), \tag{2}$$

where the averaging is performed over all the K_{M_j} possible transmit vectors $\mathbf{s}^{(j)}$ corresponding to the alphabet of the candidate modulation type M_j. For an ideal scenario where the channel matrix and the noise variance are perfectly known a-priori, the so-called average likelihood ratio test (ALRT) classifier is obtained by maximizing the natural logarithm of ALF wrt. the modulation type [6], i.e.:

$$\hat{M} = \arg\max_{M_j \in \mathcal{M}} (\log \Lambda(\mathbf{Y}|\mathbf{H}, \sigma^2, M_j)). \tag{3}$$

While not applicable in practice due to the requirement of perfect knowledge of the parameters $\mathbf{H}$ and σ^2, ALRT can be considered as optimal in the bayesian sense and its performance can be regarded as an upper bound to the MIMO AMC problem [1]. All the sub-optimal but practically more relevant likelihood-based MIMO AMC algorithms in the literature are essentially based on the ALRT, substituting some or all of the unknown parameters with their blind estimates and approximating the ALF to some degree for each individual hypothesis [1]. E.g., the HLRT classifier proposed in [6] employs an independent component analysis (ICA) based approach for blindly estimating the channel matrix, making use of the fact that the permutation ambiguity inherent to the ICA algorithms is irrelevant to the AMC problem, when all the transmit antennas employ the same modulation, and removing the remaining ICA specific phase ambiguities by employing a blind phase estimation algorithm tailored for each hypothesized modulation type individually, for which the likelihood function needs to be evaluated. However, this ICA based approach makes the assumption that the transmitted symbol streams are statistically independent, both in time index and across the transmit antennas, which is only valid for spatial multiplexing MIMO transmission. In the case of spatial modulation, signal streams transmitted from individual transmit antennas are highly statistically dependent, since in any given transmission interval, only a single transmit antenna is active while the symbols transmitted from the remaining antennas are equal to 0. Thus, the class of SpM signals is not in conformance with the ICA model, making any ICA based AMC approach as in [6] unsuitable. Furthermore, no blind channel matrix estimation methods are available for any member of the family of the SpM in the existing literature.

In the following, a classification strategy for the BSSK modulation, a special case of SpM, is presented, that extends the likelihood based approach in [6] to include the BSSK modulation by splitting the hypothesis corresponding to the BSSK into two equiprobable sub-hypotheses. This approach enables the approximation of the ALF for each of the sub-hypotheses in absence of a-priori information on the channel matrix and noise variance, resulting in a MAP classifier

III. Binary Space Shift Keying Modulation

The space shift keying (SSK) modulation is a special case of SpM, where the antenna indices are used as the only means to transmit information [5]. Thus, a K'ary SSK modulation requires a MIMO transmitter with $N_t = K$ transmit antennas in order to transmit $\log_2(K)$ bits for each channel use, and its alphabet consists of all the N_t vectors of length N_t with all the entries are equal to zero except at the position corresponding to the activated antenna, where the entry is a constant, e.g. for the binary SSK (BSSK) modulation, the set of possible transmit vectors is given as $M_{BSSK} = \{\sqrt{2}[1 \quad 0]^T, \sqrt{2}[0 \quad 1]^T\}$ Clearly, the individual unit power signal streams from each antenna $s_1[k]$ and $s_2[k]$ in a BSSK transmission exhibit a complete statistical dependence, i.e. given one of the symbols at a specific time index k, the other one is completely determined. Counterinitutively, this completely dependent signal structure can be exploited for the AMC of BSSK signals.

IV. The Proposed BSSK Classifier

Let $\mathbf{G}$ be the unitary and involutory matrix given as

$$\mathbf{G} = \frac{1}{\sqrt{2}} \begin{bmatrix} -1 & 1 \\ 1 & 1 \end{bmatrix}. \tag{4}$$

It can be shown that the random vector sequence $\mathbf{s}[k]$ generated by the BSSK modulation can be transformed into a random vector sequence $\mathbf{s}'[k] = [s'_1[k], s'_2[k]]^T$ with mutually statistically independent unit power components $s'_1[k]$ and $s'_2[k]$ by the linear transformation

$$\mathbf{s}'[k] = \mathbf{G}\mathbf{s}[k], \tag{5}$$

where $\mathbf{s}'[k] \in \{[-1 \quad 1]^T, [1 \quad 1]^T\}$ with equal probability. Thus, the first component of the transformed signal vector $s'_1[k] \in \{-1, 1\}$ can be regarded as a binary phase shift keying (BPSK) modulated sequence whereas the second component is essentially a constant sequence of ones, i.e. $s'_2[k] = 1$ $\forall k$, statistically independent from $s'_1[k]$. This statistical independence of the transformed signal components can be exploited to extend the ICA based AMC approach in [6], designed for spatial multiplexing MIMO systems employing conventional linear modulations, to MIMO systems employing BSSK modulation.

1) Blind estimation of the Channel Matrix: The ICA approach to the blind estimation of the channel matrix is based on the existence of statistically independent signal components in the received noisy signal mix $\mathbf{y}[k]$. ICA algorithms found in the literature, such as the well known JADE algorithm [7], are iterative algorithms maximizing an objective function that only characterizes the statistical independence of the separated signal components, which, being invariant to the phase and order of those components, leads to the well known permutation and phase rotation ambiguities in the separated sequences [1]. Since there exists a unitary linear transformation $\mathbf{G}$ that transforms the transmitted BSSK vector sequence $\mathbf{s}[k]$ with statistically dependent components, into a vector sequence $\mathbf{s}'[k]$ with independent components, an ICA based channel estimation approach implemented on the received signal employing BSSK modulation will generate a pre-estimate of the actual channel matrix $\tilde{\mathbf{H}}$ such that the transformation

$$\tilde{\mathbf{s}}'[k] = (\tilde{\mathbf{H}}^\dagger \tilde{\mathbf{H}})^{-1} \tilde{\mathbf{H}}^\dagger \mathbf{y}[k], \tag{6}$$

separates the received signal vector $\mathbf{y}[k]$ into those independent components, i.e. the components of $\tilde{\mathbf{s}}'[k] = [\tilde{s}_1[k], \tilde{s}_2[k]]^T$ are noisy, phase rotated and possibly permutated versions of the components of the transformed transmit signal vector $\mathbf{s}'[k]$ given in equation (5), i.e.:

$$\tilde{s}_m[k] = e^{-j\theta_l} s'_l[k] + v_l[k] \tag{7}$$

where $m, l \in \{1, 2\}$ but m not necessarily equal to l due to the permutation ambiguity, θ_l is the random phase offset and $v_l[k]$

is a noise term. Fig.1 shows the separated components of the transformed signal vector $\tilde{\mathbf{s}}'[k]$ for a BSSK signal with an SNR of 15 dB generated using the JADE algorithm. The recovered signal $\tilde{s}_1[k]$ corresponding to the constant component $s'_2[k]$ (Fig. 1(a)) and $\tilde{s}_2[k]$ corresponding to the BPSK modulated component $s'_1[k]$ (Fig.1 (b)) are clearly visible, distorted by noise, phase offsets and permutation. Using (5), (6) and (7) the pre-estimate of the channel matrix generated by the JADE algorithm for a BSSK signal can be represented as (ignoring the channel estimation errors)

$$\tilde{\mathbf{H}} = \mathbf{HGP\Theta}, \tag{8}$$

where $\mathbf{P}$ is a random 2×2 permutation matrix, $\mathbf{\Theta}$ is a 2×2 diagonal matrix with nonzero elements $[\mathbf{\Theta}]_{l,l}{=}e^{j\theta_l}$ and $\mathbf{G}$ is as defined in eq. (4). In contrast to the spatial multiplexing case considered in [6], where the components of the transmit vector are identically distributed, the presence of the permutation ambiguity is highly relevant to the AMC problem for the BSSK, since the transformed components $s'_1[k]$ and $s'_2[k]$ have different probability distributions, and this asymmetry must be taken into account in the design of the AMC strategy.

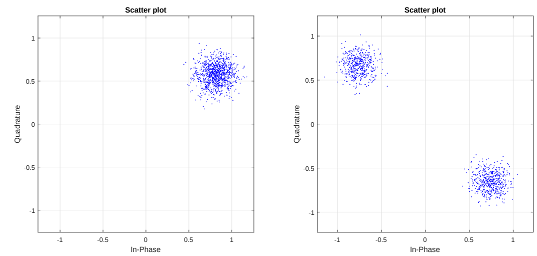
2) Effect of the permutation ambiguity: Since $N_t = 2$, the permutation ambiguity inherent to the JADE algorithm characterized by the 2×2 random permutation matrix $\mathbf{P}$ results in the exchange of order in the two components of $\tilde{\mathbf{s}}'[k]$ with a probability of occurrance 0.5 for each estimation run, as confirmed by extensive simulation experiments. Due to the difference in the probability distributions of the components of $\mathbf{s}'[k]$, this randomly occurring permutation directly affects the ALF. Since this ambiguity cannot be resolved prior to the classification, we propose to divide the hypothesis M_{BSSK} into two distinct equiprobable sub-hypotheses: M_0, where $\mathbf{P} = \mathbf{P_0} = \mathbf{I}_2$, the 2×2 identity matrix representing the case where no permutation takes place and M_1, where $\mathbf{P} = \mathbf{P}_1$ is the permutation matrix generated by interchanging the rows of $\mathbf{I}_2$, representing the case where the order of the components is exchanged. Clearly, estimation of the phase offsets corresponding to each component $\tilde{s}'_1[k]$ and $\tilde{s}'_2[k]$, calculation of the final channel matrix estimate, and the evaluation of the ALF needs to be performed for both sub-hypotheses individually.

3) Blind Estimation of the Phase Offsets: In order to resolve the phase ambiguity represented by $\mathbf{\Theta}$ we propose to employ the moment based blind phase estimation algorithm proposed in [8] both at the BPSK modulated component and the constant component of $\tilde{\mathbf{s}}'[k]$. Treating the constant signal component as a 2π rotationally symmetric constellation, the l'th diagonal element of the phase matrix estimate $\hat{\theta}_l^{(j)} = [\hat{\mathbf{\Theta}}_j]_{l,l}$ for the sub-hypothesis M_j, $j = 0, 1$ is given as:

$$\hat{\theta}_l^{(j)} = -\frac{1}{Q_l^{(j)}} \arg\Big(\sum_{k=1}^{N} \tilde{s}'_l[k]^{Q_l^{(j)}}\Big), \tag{9}$$

where $Q_l^{(j)} = 2$ for the BPSK component, and for the constant component $Q_l^{(j)} = 1$ needs to be chosen for each particular sub-hypothesis. The final estimate of the channel matrix for the sub-hypothesis M_j, $j =$ 0,1 is formed as:

$$\hat{\mathbf{H}}_j = \tilde{\mathbf{H}}\hat{\mathbf{\Theta}}_{\mathbf{j}}^{-1}\mathbf{P}_{\mathbf{j}}^{-1}\mathbf{G}^{-1} \tag{10}$$



(a) $\tilde{s}'_1[k]$ (b) $\tilde{s}'_2[k]$

Fig. 1: The components of $\tilde{\mathbf{s}}'[k]$ recovered using the JADE algorithm, with phase and permutation ambiguities.

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4) Blind Estimation of the noise variance: The second unknown parameter required for the evaluation of the ALF is the noise variance σ^2. It can be easily shown that, for all the modulation types considered in this work, a method-of-moments estimator for the noise variance for hypothesis M_j can be given as

$$\hat{\sigma}_j^2 = \frac{1}{2} trace\Big(\hat{\mathbf{H}}_j^{\dagger}\hat{\mathbf{H}}_j(\hat{\mathbf{\Sigma}} - \mathbf{I})\Big) \tag{11}$$

where $\hat{\mathbf{\Sigma}}$ is the sample covariance matrix estimate of the transmit signal recovered with the blind channel estimate $\hat{\mathbf{H}}_j$ using equation (6).

5) The Classification: We consider a classification scenario, where the BSSK is one of the L MIMO modulations in the set of possible modulation types $\mathcal{M}$, with an a-priori probability of $1/L$. Without loss of generality, we assume that all the $L-1$ modulation types in $\mathcal{M}$, other than the BSSK, are conventional linear modulation types transmitted with spatial multiplexing. Since the approximation of the ALF for the BSSK requires the consideration of two equiprobable sub-hypotheses M_0 and M_1 due to the presence of the permutation ambiguity as described above, we propose to treat those sub-hypotheses separately and to perform the classification within the augmented set $\mathcal{M}'$ with $L+1$ hypotheses containing M_0 and M_1 corresponding to BSSK, without and with permutation, respectively, each with an a-priori probability of $1/2L$, and all the remaining hypotheses M_j, $j = 2$ to L, each corresponding to one of the remaining $L-1$ modulations. Clearly, in contrast to $\mathcal{M}$ the hypotheses in $\mathcal{M}'$ are no longer equiprobable. Thus, the maximum likelihood approach of (3) needs to be replaced with a maximum a-posteriori classifier, considering the different a-priori probabilities of the hypotheses in $\mathcal{M}'$. The resulting classifier is given as:

$$\hat{M} = \arg\max_{M_j \in \mathcal{M}'} \{\log\big(P(M_j)\Lambda(\mathbf{Y}|\hat{\mathbf{H}}_j, \hat{\sigma}_j^2, M_j)\big\} \tag{12}$$

Where $P(M_j)$ represents the a-priori probability of the hypothesis M_j and is equal to $1/2L$ for $j = 0$ and 1, and $1/L$ otherwise. The final decision is made by considering that the classifier has decided for BSSK, if one of the sub-hypotheses corresponding to the BSSK, i.e. $\hat{M} = M_0$ or M_1 is chosen by

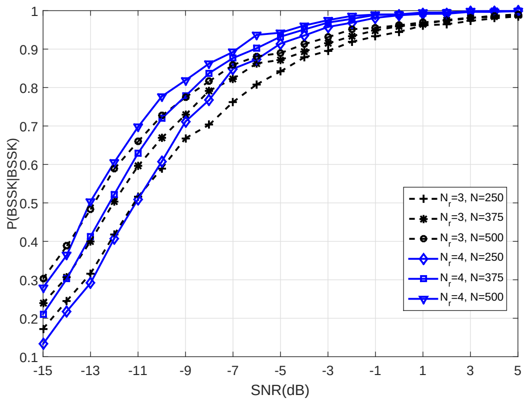

Fig. 2: The probability of correct classification of the proposed algorithm for the BSSK modulation, $P(BSSK|BSSK)$.

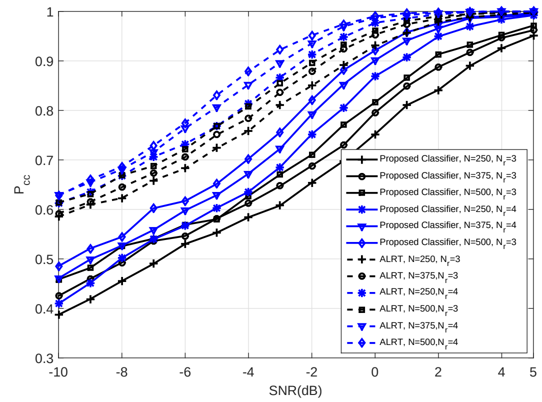

Fig. 3: The average probability of correct classification P_{cc} of the proposed classifier compared to the ideal ALRT classifier.

(12). The decisions for the remaining hypotheses are performed as usual. For the evaluation of the ALF for the hypotheses M_0 and M_1, $\hat{\mathbf{H}}_j$ is estimated using the methodology described above, whereas for the remaining conventional modulation types in $\mathcal{M}'$, the channel estimation method proposed in [6] is employed. Note that the proposed method for the approximation of the ALF for BSSK in the non-cooperative case and the proposed MAP based modification of the classifier in order to include the BSSK can be applied to any likelihood based MIMO AMC scenario with arbitrary alternative hypotheses.

V. Classification Results

In this section, the performance of the proposed AMC strategy is evaluated via Monte Carlo simulations. We consider the set of possible modulation types $\mathcal{M} = \{BSSK, BPSK, QPSK, 8PSK, 16QAM\}$, where the latter four conventional modulation types are transmitted using spatial multiplexing with $N_t = 2$. For each modulation type, 3000 Monte Carlo trials have been performed per SNR. Without loss of generality, we assume unit power transmit signals from each antenna, hence, the average signal-to-noise ratio is expressed as SNR=$\frac{N_t}{\sigma^2}$ [6], [4]. The simulations have been performed for $N_r = 3$ and 4, and observation lengths of $N = 250$, 375 and 500. Fig.2 displays the probability of correct classification of the algorithm for BSSK modulation, denoted as $P(BSSK|BSSK)$, whereas Fig.3 displays the average probability of the correct classification of the algorithm, denoted as P_{cc}, the individual classification probabilities for each modulation averaged over all the possible modulation types within the set $\mathcal{M}$, as in [4]. For comparison, the P_{cc} results from the ideal ALRT classifier are also provided for the same set, which constitute an upper performance bound [6]. The results exhibit a high classification performance for BSSK even in the low SNR regime and relatively small values of N. A comparison of Figs. 2 and 3 reveals a considerably higher classification probability for the BSSK compared to the overall P_{cc}, which is the result of a better discrimination performance between the BSSK and the conventional modulations in $\mathcal{M}$ compared to the discrimination between conventional modulation types themselves. As expected, the performance of the algorithm increases with increasing N and N_r.

VI. Conclusion

This work considers, for the first time in the literature, the AMC problem for a modulation type belonging to the family of spatial modulations, the BSSK. The proposed maximum a-posteriori based AMC approach enables the classification of the BSSK modulation in absence of a-priori information on the channel matrix and noise variance, making it especially suitable for non-cooperative application scenarios. The numerical results show that the proposed method exhibits a good classification performance even in the low SNR regime and for short observation intervals. Our future research will include the extension of the proposed approach to other types of SpM and the design of blind channel matrix estimation methods exploiting the sparsity of the SpM signals.

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